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# Satellite Data Applications for Sustainable Energy Transitions

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Transitioning to a sustainable energy system poses a massive challenge to communities, nations, and the global economy in the next decade and beyond. A growing portfolio of satellite data products is available to support this transition. Satellite data complement other information sources to provide a more complete picture of the global energy system, often with continuous spatial coverage over targeted areas or even the entire Earth. We find that satellite data are already being applied to a wide range of energy issues with varying information needs, from planning and operation of renewable energy projects, to tracking changing patterns in energy access and use, to monitoring environmental impacts and verifying the effectiveness of emissions reduction efforts. While satellite data could play a larger role throughout the policy and planning lifecycle, there are technical, social, and structural barriers to their increased use. We conclude with a discussion of opportunities for satellite data applications to energy and recommendations for research to maximize the value of satellite data for sustainable energy transitions.

**Keywords: energy, satellite, sustainability, decision-making, data**

## INTRODUCTION

Actors across the energy system – from local, state, and national governments to electric utilities, technology developers, and a wide variety of energy end users – are grappling with options to limit the rise in global temperature to well below 2°C (and preferably 1.5°C) and achieve net-zero carbon dioxide ($CO_2$) emissions targets (Hultman et al., 2020; Klemun et al., 2020). Meeting

these ambitious goals will require far-reaching energy transitions in electricity, transportation, buildings, and industry (IPCC, 2018; Cui et al., 2019). Climate change is also shifting patterns in energy demand and increasing disruptions in energy access due to damage to infrastructure caused by extreme temperatures, floods, droughts, hurricanes, and other disasters. New sources of information are needed to support sustainable energy transitions and evaluate whether energy planning and policy decisions are effective and equitable (Carley and Konisky, 2020). By providing observations of Earth from space, satellite data hold new potential to address these global challenges.

Since the first satellite images were made publicly available in 1972, applications of satellite data have expanded significantly (Davis, 2007; Inman et al., 2013). Satellite data vary in spatial resolution (from tens of kilometers to less than a meter), frequency of observations (from weeks to minutes), and coverage (from continuous observations from geostationary satellites to global coverage from polar-orbiting satellites) (Medina-Lopez et al., 2021). There are trade-offs across these design features, with free, publicly available data from government sources tending toward global coverage and a growing number of private companies offering targeted observations of particular locations. Cloud-computing services further enhance the prospects for widespread use of satellite data by allowing broad user communities to process large amounts of data on the fly (Gorelick et al., 2017). Beyond the satellite technology itself, research has also advanced applications of satellite data to decision-making through comparisons with other data sources, integration with models, and case studies applying satellite data to particular contexts and examining barriers to use (Milford and Knight, 2017; Holloway et al., 2018)[1,2].

Decisions related to energy supply, demand, impacts, and resilience all stand to benefit from growing integration of satellite data. Satellite applications for energy supply include mapping renewable resource potential to support infrastructure siting, development, and maintenance. Applications for energy demand include assessing energy use patterns to predict future needs and identify locations with unserved demand, both on an ongoing basis and in the aftermath of power disruptions. Applications for energy impacts include monitoring the effects of energy use on climate, air quality, and water and land systems, as well as efforts to reduce these impacts. Existing information sources used in the past have often been limited in spatial coverage and accessibility for a diversity of stakeholders and decision-making needs. These stakeholders also frequently lack access to timely information needed to support cross-cutting reliability and resilience goals, as well as disaster response. Expanded use of satellite data can now help address these information gaps.

This paper reviews the current state of satellite data for energy applications and potential future directions for research. We focus specifically on satellite tools for remote sensing because of their broad scale and routine measurements, as well as their underutilized potential for energy policy and planning. Each section presents an overview of conceptual and practical applications of satellite data, drawing primarily from the peer-reviewed literature. Applications vary in their level of maturity, from well-established uses with strong links to decision frameworks to emerging areas where there are significant technical, social, and/or structural barriers to applying satellite data to decision-making. While previous work examines satellite data for various energy applications in isolation, there is significant potential to increase the value of satellite data for energy decision needs by bridging insights across energy issues. Understanding the value and potential of satellite data to address energy-related challenges is particularly salient given the speed and scale of energy transitions required to mitigate and adapt to climate change.

**Abbreviations:** ABI, Advanced Baseline Imager; AHI, Advanced Himawari Imager; AIMM, Alternative Approved Instrument Monitoring Method; AMEL, Alternative Means of Emission Limitation; AMSR-E and AMSR2, Advanced Microwave Scanning Radiometers; ARLs, Application Readiness Levels; ASAR, Advanced Synthetic Aperture Radar; ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; CEMS, Continuous Emissions Monitoring System; CERES, Clouds and Earth's Radiant Energy System; CO, Carbon monoxide; $CO_2$, Carbon dioxide; CO2M, Copernicus Carbon Dioxide Monitoring mission; COP26, 2021 United Nations Climate Change Conference; DMSP-OLS, Defense Meteorological Satellite Program-Operational Linescan System; DNB, VIIRS Day Night Band; DOE, U.S. Department of Energy; EOSDIS, Earth Observing System Data and Information System; EPA, U.S. Environmental Protection Agency; EPRI, Electric Power Research Institute; ESA, European Space Agency; ETM+, The Enhanced Thematic Mapper Plus; EUMETSAT, European Organization for the Exploitation of Meteorological Satellites; FIRMS, NASA's Fire Information for Resource Management System; GEMS, Geostationary Environmental Monitoring Spectrometer; GeoCarb, Geostationary Carbon Cycle Observatory; GOES, Geostationary Operational Environmental Satellite; GOME-2, Global Ozone Monitoring Experiment-2; GOSAT, Greenhouse Gas Observing Satellite; IMEO, International Methane Emissions Observatory; InSAR, Interferometric Synthetic Aperture Radar; ISS, International Space Station; LANCE, Land, Atmosphere Near-real-time Capability for EOS; LDAR, Leak Detection and Repair; MERRA-2, Modern-Era Retrospective analysis for Research and Applications, Version 2; MODIS, Moderate Resolution Imaging Spectroradiometer; MSG, Meteosat Second Generation; MSI, European Sentinel-2 MultiSpectral Instrument; MTG, European Meteosat Third Generation; NASA, National Aeronautics and Space Administration; NMVOC, Methane and Non-methane Volatile Organic Compounds; NO, Nitric oxides; $NO_2$, Nitrogen dioxide; NOAA, National Oceanic and Atmospheric Administration; NOAA ASCAT, National Oceanic and Atmospheric Administration Advanced Scatterometer; $NO_X$, Nitrogen oxides; NREL, National Renewable Energy Laboratory; NSRDB, U.S. National Solar Radiation Data Base; NTL, Nighttime Light; OCO-2, Orbiting Carbon Observatory-2; OLI, Operational Land Imager; OMI, Ozone Monitoring Instrument; POWER, NASA Prediction Of Worldwide Energy Resources project; PV, Photovoltaic; ROW, right-of-way; RSPO, Roundtable for Sustainable Palm Oil; SAR, Synthetic Aperture Radar; SCIAMACHY, SCanning Imaging Absorption spectroMeter for Atmospheric CHartographY; SMAP, Soil Moisture Active Passive; SMMR, Scanning Multichannel Microwave Radiometer; SRON, Netherlands Institute for Space Research; SSMI, Special Sensor Microwave Imager; Suomi NPP satellite, Suomi National Polar-orbiting Partnership; TEMPO, Tropospheric Emissions: Monitoring of Pollution; TRMM, Tropical Rainfall Measuring Mission; TROPOMI, Tropospheric Monitoring Instrument; UNEP, United Nations Environment Program; UVN, UV/Visible/Near-infrared; VCD, Vertical Column Density; VIIRS, Visible Infrared Imaging Radiometer Suite; VOC, Volatile Organic Compounds; WHO, World Health Organization.

[1]EPRI. Application of Image Processing Algorithms to Improve Predictive Reliability Assessments: Identifying Physical Threats Using GIS and Satellite Imagery. https://www.epri.com/research/products/000000003002018884.

[2]EPRI. Program on Technology Innovation: Using Hyperspectral Imagery and Artificial Intelligence (AI) to Detect Stressed and Dead Trees. https://www.epri.com/research/products/000000003002022770.

The author team represents experts in a wide variety of energy and satellite topics from academia, government organizations, research institutions, and private companies. Following the introduction, we discuss satellite data applications in energy supply, energy demand, energy impacts, and energy resilience. We then describe an example of a satellite data distribution platform for energy users. We conclude with a discussion of the potential and limitations of satellite data across energy applications and recommendations for research to enhance the usefulness of satellite data for energy stakeholders.

# ENERGY SUPPLY

Many studies have quantified the enormous expansion in renewable energy needed to achieve global climate policy goals (IPCC, 2022). Satellite data can support the development, deployment, and forecasting of renewable energy sources such as bioenergy, hydropower, solar photovoltaics, wind turbines, and geothermal energy. Beyond assessing the potential for new systems, satellite data can also help optimize performance and track the rate of technology adoption.

## Bioenergy Resources and Production

Satellite data are a leading source of information for policy and planning decisions related to bioenergy feedstock supply and productivity. Space-based data routinely inform assessments of biofuel feedstock availability and land use impacts, as well as potential competition with food production and impacts on other ecosystem goods and services. Productivity can be quantified from satellite observations of vegetation greenness and further constrained or refined using indirect satellite-based information on climate, soil conditions, and other co-determinants of productivity. Satellite-based estimates of land availability and supply have been used by industry, policymakers, and other bioenergy stakeholders in the evaluation and design of production systems and regulations.

Data on land cover have been used to identify abandoned agricultural lands with potential to support bioenergy feedstock production (Zumkehr and Campbell, 2013; Baxter and Calvert, 2017; Goga et al., 2019; Næss et al., 2021) and to screen for land that may be deemed as marginal for food production (Nalepa and Bauer, 2012; Kang et al., 2013; Khanna et al., 2021) due to economic instability (Jiang et al., 2021), environmental sensitivity (Wang et al., 2020), and biophysical limitations in climate, soils, or topography (Gelfand et al., 2013; Gu and Wylie, 2016). For example, satellite-based productivity thresholds on low-yielding lands have been used to identify marginal areas for second generation bioenergy production (Longato et al., 2019). From local to global scales, estimates of the maximum potential production of bioenergy can support energy planning and policy (Cai et al., 2011; Smith et al., 2012; Haberl et al., 2013). Bioenergy producers or investors can also use estimates of local feedstock supply (e.g., corn) to identify locations for siting future biorefineries.

Satellite-constrained estimates of total bioenergy production potential have also been used to project the contribution that bioenergy might make toward global climate policy goals or to meet national pledges to the Paris Agreement (IPCC, 2018; Creutzig et al., 2021). Policies such as the Low Carbon Fuel Standard and the Renewable Fuel Standard in the U.S. have used satellite-based estimates of land use change associated with bioenergy to measure and regulate greenhouse gas emissions intensity associated with different bioenergy systems, as well as to determine the eligibility of various fuels in each regulation (US EPA, 2010; Leland et al., 2018). Other work has used field-level remote sensing data to analyze changes in bioenergy feedstock supply caused by these policies, finding that the U.S. Renewable Fuel Standard, for example, led to an 8.7% increase in U.S. corn cultivation (Lark et al., 2022).

New data sources and advances in data science will open the door for highly detailed and precise ground-based data to complement data from satellites. For example, parcel-level data on land ownership and sales could enable a more refined understanding of how producers respond to policy and market incentives, and productivity measurements collected directly from agricultural equipment could significantly expand data availability. Nonetheless, satellite data will continue to provide irreplaceable information on bioenergy production that covers large geographic extents in a consistent manner over time, particularly with the increased availability of high-quality, high-resolution, and low-cost commercial and small-satellite platforms.

## Hydropower and Water Supply

Satellite data are commonly used in water resource assessment for planning hydropower projects, monitoring reservoir size, and evaluating the environmental impacts of rerouting or damming water. Hydrological and hydrometeorological variables, such as precipitation, snow extent, soil moisture, runoff, and evapotranspiration, influence the availability of water resources to support power generation. Hydropower currently accounts for ∼60% of global renewable electricity production and is projected to play a major role in flexible power systems as the world transitions to cleaner energy sources (International Hydropower Association, 2021). Planned hydroelectric projects also dominate the renewable energy sector in sub-Saharan Africa, where significant untapped potential exists (Stiles and Murove, 2019), offering opportunities for new uses of satellite data products (Leibrand et al., 2019). Tracking and monitoring water resources is critical to ensuring and managing future water supply, especially given projected changes in water resources due to climate change (Fletcher et al., 2019).

Landsat and Terra satellites have been collecting environmental and climate data for several decades and provide a long historical record to help identify trends and spatial patterns in river flow, snow melt, land cover, and other variables that impact water availability, which is useful in decision-making for hydropower operations (see **Figure 1** for an example). Other satellites provide data in near real time, such as the National Aeronautics and Space Administration's (NASA's) Soil Moisture Active Passive (SMAP) mission, which measures global soil moisture in increments as short as 3 hours, with a latency of 24 hours and a revisit time of 2–3 days, thus reducing the need for field evaluation.

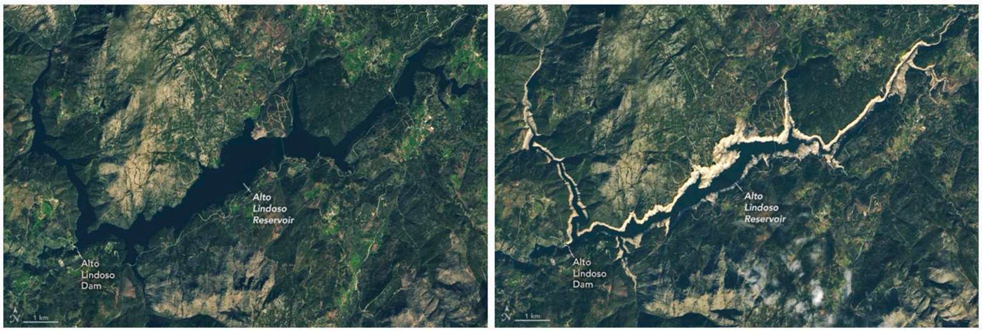


**FIGURE 1 |** Tracking the impact of drought on a hydropower reservoir at the Alto Lindoso Dam in Portugal from March 6, 2021 **(L)** to February 5, 2022 **(R)**, using Landsat 8 data [Credit: NASA Earth Observatory image by Lauren Dauphin, using Landsat data from the U.S. Geological Survey (NASA Earth Observatory, 2022)].

Satellite-based data on groundwater, surface water height and extent, and precipitation may be used to assess seasonal and historical changes in water storage. Freeze-thaw data derived from satellite microwave radiometry from NASA's Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave/Imager (SSM/I), and Advanced Microwave Scanning Radiometers (AMSR-E and AMSR2) have been used to evaluate the dynamics of seasonal snow, ice melt, and soil thaw as a proxy for measuring water mobility over time (Kimball and McDonald, 2020). Taken together, satellite-derived hydrological and hydrometeorological data can identify trends in water availability, potential for flooding and drought, and other environmental aspects for improved decision-making in the hydropower sector.

Machine learning and data assimilation are advancing data analysis to improve observations for hydropower in areas where ground-based data are scarce. For example, machine learning has been combined with near-real-time rainfall data from NASA's Tropical Rainfall Measuring Mission (TRMM) and soil moisture data from the National Oceanic and Atmospheric Administration's (NOAA's) Advanced Scatterometer (ASCAT) to simulate streamflow in India (Kumar et al., 2021). Machine learning with various satellite-derived hydrometeorological variables has also been used to calculate streamflow in the Hanjiang River in China (He et al., 2021). Data assimilation, another approach to data fusion, has also improved land surface model predictions of water storage, particularly when multiple satellite data products are combined (Khaki et al., 2020).

There are new opportunities to use satellite data for hydropower planning and management (International Hydropower Association, 2020). NASA, NOAA, the European Space Agency (ESA), and other Earth observing organizations provide open-source data and offer training on how to apply data to real-world decisions, working to reduce barriers to use and accessibility. The value of these data is especially high in regions with gaps in ground-based data and with high climate variability, where uncertainties in water resources present challenges for hydropower planning and operations.

## Solar Photovoltaic Systems

Satellite data have long been used to measure annual solar insolation in conjunction with ground-based pyranometer data (Perez et al., 2013). For example, the U.S. National Solar Radiation Data Base (NSRDB) from the National Renewable Energy Laboratory (NREL) uses data from the NOAA Geostationary Operational Environmental Satellite (GOES), NASA Moderate Resolution Imaging Spectroradiometer (MODIS) instrument, and NASA's Modern-Era Retrospective analysis for Research and Applications Version 2 (MERRA-2) assimilation model to create a dataset that shows historical levels of solar energy resources in any location in the U.S. (Sengupta et al., 2018). The multiple source dataset goes back to 1998 at a temporal resolution of half an hour. Additionally, global solar radiation data are made available back to the early 1980's using fused geosynchronous and polar orbiting satellites, including data products available since 2020 from NASA's Clouds and Earth's Radiance Energy System (CERES) (Zhang et al., 2004; Rutan et al., 2015; Karlsson et al., 2017; Stackhouse et al., 2021).

With increased penetration of variable wind and solar power on the grid, there is a new focus on system performance and short-term wind and solar resource forcasting (Janjai et al., 2011; Pfenninger and Staffell, 2016; Peters et al., 2018). For example, machine learning has been used to predict cloud velocities to understand where drops in photovoltaic (PV) system production might occur (Cheng et al., 2022), and satellite-derived aerosol levels may be used to assess the impact of air pollution on PV arrays (see example in **Figure 2**) (Li et al., 2017). Local decision-makers can also use satellite-derived maps to inform cost-effective renewable energy project upkeep, such as vegetation management (Yu et al., 2018).

Satellite data can also be used to track renewable energy deployment, assess solar access disparities, and potentially support third party validation of renewable energy adoption

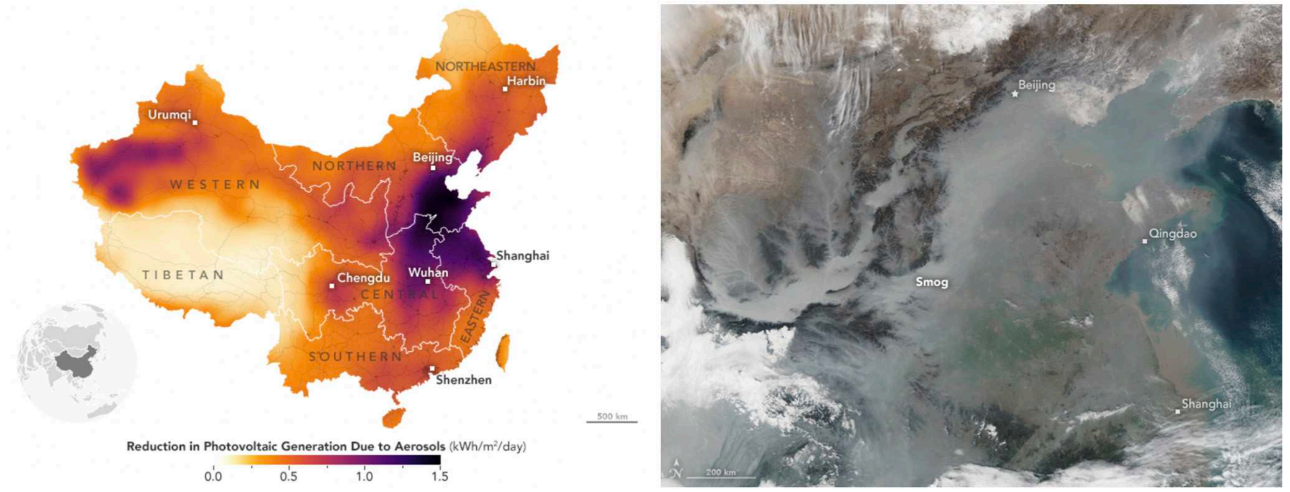


**FIGURE 2 | (L)** Impact of aerosols on the average amount of radiation reaching the land surface of China between 2003 and 2014 [Credit: Joshua Stevens, NASA Earth Observatory, using data from Li et al. (2017)]. **(R)** Natural-color image of haze over eastern China from the Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi National Polar-orbiting Partnership (NPP) satellite on January 25, 2017. (Credit: Jeff Schmaltz, NASA, LANCE/EOSDIS).

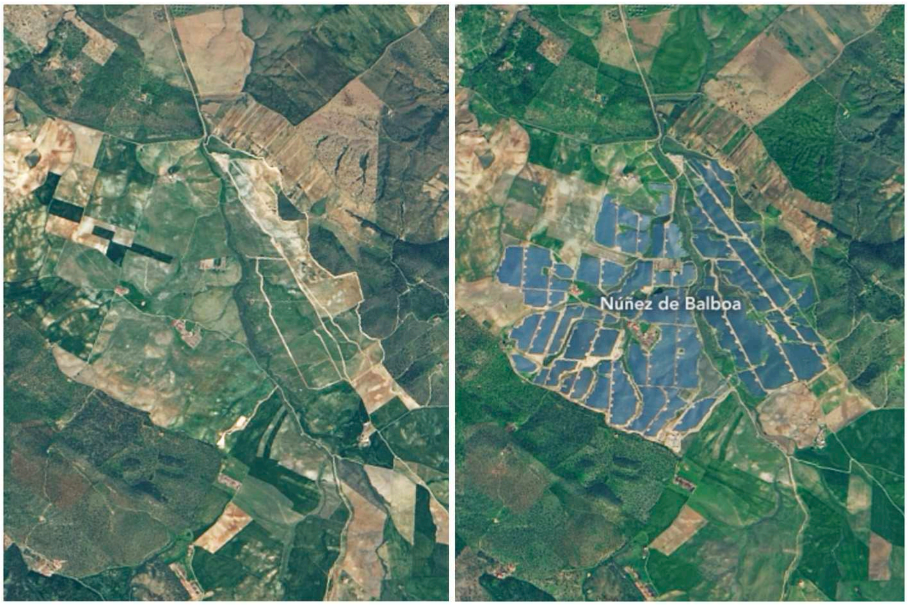


**FIGURE 3 |** Satellite images of a 500 MW solar power plant on the Iberian Peninsula. **(L)** shows imaging before installation in 2020, **(R)** shows imaging after installation (Credit: NASA Earth Observatory image by Lauren Dauphin, using Landsat data from the U.S. Geological Survey).

under climate agreements (see example in **Figure 3**)[3]. Standard solar PV accounting methods generally focus on limited regions and often miss smaller systems. Satellite image processing offers an efficient method for tracking growth in solar energy across large geographic areas (Kruitwagen et al., 2021), but smaller residential and microgrid systems are still difficult to track (Ishii et al., 2016).

[3]United Nations. Net Zero Coalition. https://www.un.org/en/climatechange/net-zero-coalition.

## Offshore Wind Projects

Using traditional *in-situ* measurements such as buoys to measure offshore wind resources is expensive, time consuming, and limited in its geographic coverage. As an alternative, synthetic aperture radar (SAR) data from satellites is being used to estimate wind power from wave heights and direction. Recent efforts

have focused on improving the SAR method's accuracy. For example, calibrating satellite data on sea winds can help improve estimates of wind speeds (Soukissian and Papadopoulos, 2015), and advanced data analysis methods like machine learning can help predict wind energy production (Majidi Nezhad et al., 2021a). To estimate wind energy at actual wind hub heights (∼100 m), near sea-surface (∼10 m) wind readings from the ESA Envisat Advanced Synthetic Aperture Radar (ASAR) are used to extrapolate wind speeds at greater elevations (Badger et al., 2016). In areas impacted by wake effects, SAR data available from missions such as the Envisat ASAR and Sentinel 1 can also measure wind speeds (Ahsbahs et al., 2018).

Although satellites cannot "see" future winds, satellite data can be used to improve forecasts of wind resource availability for wind projects (Inman et al., 2013). In offshore applications, SAR data can be used to constrain short-term weather predictions and provide temporally and spatially expansive estimates of wind speeds and wave heights (Zen et al., 2021). Both measures are important for the design, planning, and operation phases of offshore wind projects, including efficiently screening for promising offshore wind resource areas and reducing uncertainty around installation weather windows. Future areas for research include improving the spatial resolution of wave and wind detection, as the current practice is to assume similar conditions across an entire wind farm based on a limited set of estimates (Medina-Lopez et al., 2021). Additionally, inter-hour offshore wind resource forecasting is becoming more critical as coastal power grids rely on greater penetration of offshore turbines, which recent satellite products, such as ESA's Aeolus mission, will help improve (Medina-Lopez et al., 2021).

## Geothermal Energy

Satellite data is supporting the exploration and monitoring of geothermal energy sources, which have the potential to provide non-emitting baseload power (Vargas et al., 2022). Remotely sensed thermal infrared data has been used since the 1980's to detect geothermal activity and identify potential sites for geothermal plants, providing a less costly data source than field investigations (Majidi Nezhad et al., 2021b). Thermal infrared bands that are sensitive to surface temperatures are used to identify anomalies that are potentially the result of subsurface geothermal activity. Instruments that have been used for geothermal prospecting include MODIS, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Landsat's Enhanced Thematic Mapper Plus (ETM+), and SAR (Howari, 2015). For example, one recent study used ASTER data to map geothermal potential along a section of the East African Rift System, where previous mapping coverage was limited, using a combination of surface temperature estimates and indicator minerals (Hewson et al., 2020).

The coarse resolution of thermal sensors provides a means to target field activities but limits their usefulness to broader scale detection of geothermal anomalies. However, satellite data can be useful for studying geothermal potential and ground temperature recovery because of the ability to construct long-term datasets. A key tool that allows for this type of analysis is the Interferometric Synthetic Aperture Radar (InSAR) technique, which can map ground deformation through clouds and at night, providing expansive temporal and spatial coverage (Mellors et al., 2018; Majidi Nezhad et al., 2021b). For example, two years of Sentinel-1 SAR data was used to analyze Iceland's untapped geothermal energy, as well as pressure changes from geothermal fluid extraction for a new power plant (Receveur et al., 2019). Future research can look to relate satellite-derived prospecting with existing geothermal data (or exploratory drilling) to improve data relevance to future geothermal applications (Howari, 2015).

# ENERGY DEMAND

Tracking energy demand, both temporally and spatially, is critical to a just and sustainable energy transition. Nighttime lights (NTL) data have been actively used to monitor energy use and electrification and identify gaps for further policy development. With 770 million people worldwide without access to electricity, and many others lacking reliable and affordable heat and power (Hernández, 2015; Reames, 2016; IEA, 2021c), NTL data may be the most important data product to inform decisions to support energy access and restoration.

## Energy Use and Infrastructure

Nighttime lights are a widely used indicator of energy use and infrastructure (NASA Earthdata, 2021) and have been correlated with economic activity, urbanization, population density, and energy consumption and access (Falchetta and Noussan, 2019). There are two principal datasets that provide NTL. The first digital NTL dataset is available from 1992-2013 through the Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS). However, each pixel in these images has only 64 potential values, a consequence of the 6-bit radiometric resolution of the satellite instrument. Due to this limited range, the data become saturated when NTL levels are high, especially in urban areas, limiting NTL applications to planning and policy at the city scale. Limited low-light detection also curtails NTL utility in dimly lit regions such as rural areas. The 2.7 km spatial resolution further limits energy-related applications at local scales.

The second and more recent NTL dataset is developed from the VIIRS Day Night Band (DNB) onboard the Suomi-NPP satellite, launched in 2011. VIIRS NTL is a significant improvement over DMSP-OLS NTL in two ways: the spatial resolution is much improved at 750 m, and the sensor has a larger dynamic range, with improved calibration that allows for accurate measurements of very low and high intensity nighttime lights. Recent advances to harmonize the DMSP and VIIRS NTL data have made them easier to access and integrate for wider applications (Li et al., 2020a).

For scientific studies, the most robust NTL dataset is Black Marble, which uses raw VIIRS data and corrects for atmospheric and radiometric issues (Romn et al., 2018). These data are calibrated across time, validated against ground-based data, and available at daily resolution. NASA scientists are currently working on a high-definition version of Black Marble, which will allow researchers to downscale NTL data at finer

spatial resolutions by integrating Landsat and Sentinel Earth observations and street-level GIS data into the Black Marble product, and thereby improve NTL visualization in dense urban areas (NASA Goddard Space Flight Center, 2021). In 2021, the World Bank created the Light Every Night dataset, which is a complete archive of all NTL data collected over the past three decades (Min et al., 2021)[4]. Higher-resolution NTL images are available via photographs taken from the International Space Station (ISS) and the private company NOKTOsat (de Miguel et al., 2014; Noktosat, 2021). Additional sources of NTL data exist, but many are not publicly accessible (Li et al., 2019).

The combination of finer spatial, radiometric, and temporal resolutions, as well as integration of new data sources and processing techniques, can provide near-real-time estimates of energy use. To evaluate energy access, NTL data may be combined with on-the-ground information from utilities, GIS data, and local knowledge of energy access (Zhao et al., 2019). Fusing satellite data products with data from mobile phones can also support assessments of energy use, energy poverty, and disaster response (Steele et al., 2017), while NTL data combined with census data, national household surveys, or meter data can help users better understand and address inequities in energy infrastructure and access at scale (Mann et al., 2016; Pandey et al., 2022). Satellites can also identify changes in energy demand, such as those associated with COVID-19 or holidays from different cultures (Román and Stokes, 2015; Elvidge et al., 2021; Stokes and Román, 2022).

There are several important limitations to the use of NTL as an indicator of energy and other socioeconomic variables to inform policy. Broadly, NTL are an imperfect proxy for energy use and access. Current satellite data products cannot accurately measure energy use at smaller scales relevant for many policy questions, such as at household, street, or neighborhood levels, especially in high-density areas (Falchetta et al., 2020a). NTL data are less accurate for measuring electrification in areas where energy supply is intermittent, as conventional uses of NTL and other satellite observations are often binary (i.e., the lights are on or off) (Dugoua et al., 2017). Streetlights, car lights, and LED lighting may also make an area appear more or less electrified than it truly is (Zhao et al., 2019). Finally, NTL data may be more appropriate for estimating energy and other variables in some regions than others (Zhu et al., 2019a). For example, in areas with fires or oil and gas flaring, NTL may reflect these sources rather than electrification.

## Global Energy Access

Over the past few decades, countries around the world have made large investments to support the goal of universal energy access and improve the reliability of electricity supply (Aklin et al., 2018), yet access to electricity and modern cooking fuels and technologies remains low in some regions (World Bank, 2019). The main gaps are found in sub-Saharan Africa (570 million lacking electricity), Central and Southern Asia (103 million), and Southeast Asia (40 million) (World Bank, 2019). While these regional statistics provide a general understanding of the existing gap, it is critical to develop tools to map the geographic distribution and temporal dynamics of these populations to provide a fine-grained, up-to-date understanding of electricity access across the world.

Tracking of energy poverty and access has generally been carried out through household surveys administered by national governments and international organizations. Satellite-based NTL data can serve as a proxy for electricity access to support electrification planning, complementing traditional survey methods (see example in **Figure 4**) (Min et al., 2013; Burlig and Preonas, 2016; Dugoua et al., 2017; Fobi et al., 2018; Avtar et al., 2019). These data are often combined with data on population density and other socioeconomic indicators (Stokes and Seto, 2019; Zhao et al., 2019; Falchetta et al., 2020b). NTL data have shown that lack of electrification is most pronounced in countries where a large proportion of the population lives in dispersed, rural settlements with few resources (Doll and Pachauri, 2010). However, these data also suggest that energy access can decline in urban areas that were once more reliably electrified as utilities struggle to keep pace with increasing energy needs associated with rapid urbanization, especially peri-urban areas and informal settlements (Falchetta et al., 2020b).

Nighttime lights have also been combined with utility data to inform renewable energy and microgrid infrastructure planning, as well as electrification of essential services such as healthcare facilities (Korkovelos et al., 2019; Moner-Girona et al., 2019, 2021). If utility data are unavailable (e.g., after a natural disaster or in rural or low-resource settings), NTL data can be used as a proxy to estimate energy access (Fragkias et al., 2017). The stability of NTL radiance over time has also allowed it to be used to evaluate supply reliability and to measure the impact of hydroelectricity disruptions due to drought events (Arderne et al., 2020; Falchetta et al., 2020b). These studies seek to go beyond the binary classification of energy access and lack of access, which is crucial as energy poverty is a multi-dimensional challenge (Pelz et al., 2018, 2021). Thus, despite limitations of NTL data, its usefulness for understanding energy access continues to grow.

Sub-Saharan Africa stands to particularly benefit from the use of NTL data for electrification planning. Lack of energy access and unreliable electricity have hampered economic growth, and policymakers across the region face the challenge of expanding energy access to almost half the continent (IEA, 2019). Using NTL, population, and settlement data, one study estimated that between 2014 and 2019, 115 million people in sub-Saharan Africa gained access to electricity. However, in some cases, energy access did not equate to energy use, and some countries that had made strides in expanding access saw limited use in newly electrified households (Falchetta et al., 2019, 2020a). These studies highlight that increases in access must be accompanied by increases in generation and grid infrastructure to improve the quality and reliability of electricity that is delivered to households (Falchetta et al., 2020b).

Improvements to NTL data, primarily via increases in resolution and reductions in uncertainty as instruments and algorithms advance, will enable broader data use by

[4]World Bank - Light Every Night. *Registry of Open Data on AWS* https://registry.opendata.aws/wb-light-every-night/.

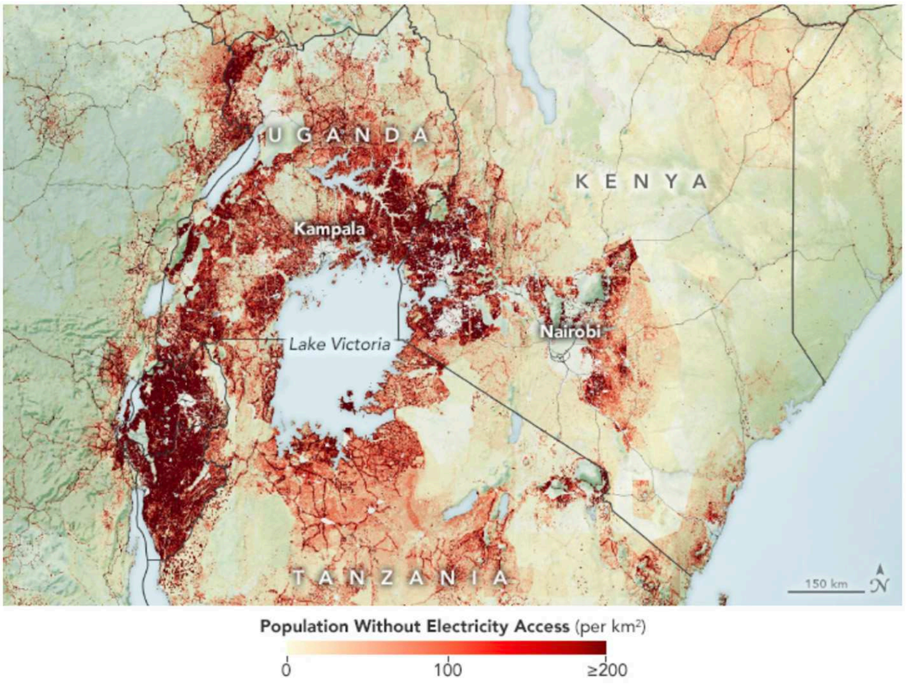


**FIGURE 4 |** Estimate of the number of people without access to electricity in East Africa using data from the VIIRS instrument on the NOAA-NASA Suomi NPP satellite, land cover type data from NASA's MODIS instrument, and data from Oak Ridge National Laboratory's LandScan. [Credit: NASA Earth Observatory image by Lauren Dauphin, using data from Falchetta et al. (2019, 2020a) (NASA Earth Observatory, 2021a)].

policymakers, utility managers, emergency response personnel, and other stakeholders. Usefulness of NTL data can be further improved with integration of GIS maps and geoprocessing tools (Dugoua et al., 2017). Data at finer resolutions will also increase the usability of NTL and expand applications in which it can be used. With higher spatial and radiometric resolution, and finer time scales of collection, researchers can start to examine a range of issues related to the quality and consistency of energy availability – not just whether energy infrastructure exists, but the frequency (reliability) of lighting and how quickly lighting is restored after a major disaster such as a hurricane (Romn et al., 2019), blackout, or conflict. Similarly, these data can be used to track the urban development process and to identify locations that have inadequate energy infrastructure (Stokes and Seto, 2019).

## Urban Areas and Urbanization

Urban areas account for approximately 75% of global final energy use, and this demand is strongly correlated with urban form and structure (Seto et al., 2014). Therefore, characterizing urban areas can inform estimates of energy demand, even at the global scale, and can be useful in planning future energy investments to support sustainability and other goals. Urban expansion can lead to categorical changes in land cover, such as when agricultural areas become urban, as well as magnitude changes, such as urban intensification. The distinction between measurement of categorical vs. magnitude changes is important because the optimal methods and reliability of estimates differ between the two. Measuring categorical change is typically easier than measuring the magnitude of urban change.

The majority of published studies have focused on mapping two-dimensional urban expansion, or outward urban growth (Zhu et al., 2019b; Reba and Seto, 2020). It is only in the past decade that the research community began to examine volumetric growth of urban areas (see **Figure 5** for an example). Three-dimensional characterization of the built environment reveals more about urban form, structure, and resource use, such as the demand for reinforced steel and concrete or embodied and operational energy use. Backscatter data from the QuikSCAT SeaWinds scatterometer have been shown to be able to characterize urban volumetric infrastructure growth for large cities (Frolking et al., 2013; Creutzig et al., 2016; Mahtta et al., 2019; Li et al., 2020b). The recent development of a time series with ERS, QuikSCAT, and ASCAT backscatter data covering three decades will enable new studies of urban built structures and their energy implications (Frolking et al., 2022).

A recent review of algorithms to detect, characterize, and monitor urban land changes found that most methods have been developed and applied for only a few regions (e.g., the U.S. and China), with 75% of studies focused on high-income or upper-middle-income countries (Reba and Seto, 2020). Furthermore, while 11% of the world's urban population lives in cities with populations greater than 5 million, 41% of studies have focused on these very large cities, whereas most future urban growth

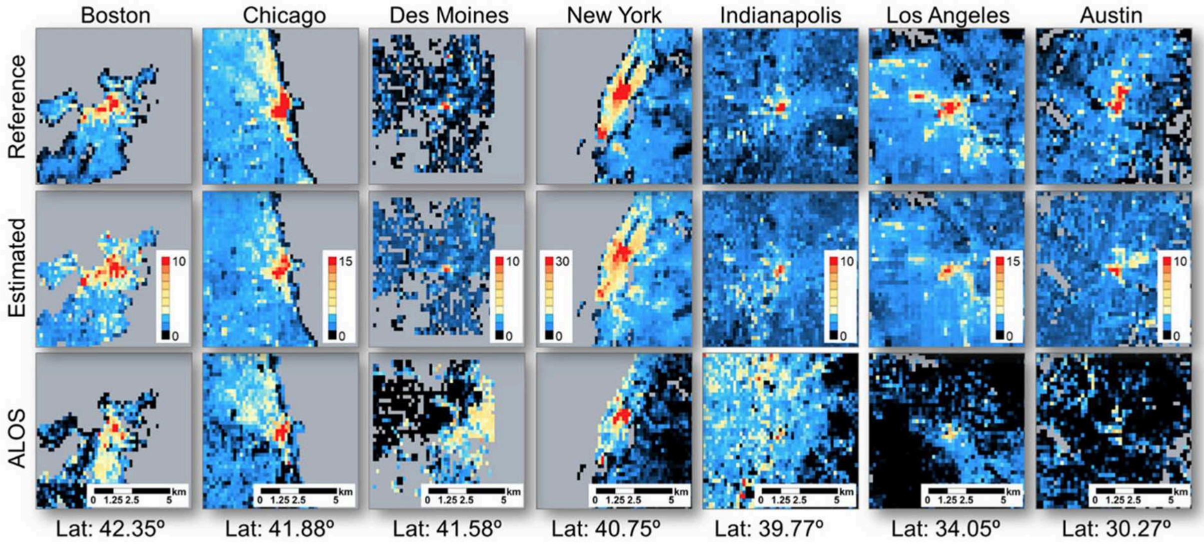


**FIGURE 5 |** Estimated spatial patterns in building heights in seven U.S. cities using Sentinel-1 data, compared to reference (non-satellite) measurements and Advanced Land Observing Satellite (ALOS) data (unit: m). Measurements are presented at 500 m resolution with a spatial extent of 20 × 20 km. Areas outside the study domain are colored as gray. [Credit: Li et al. (2020b)].

will occur in towns and cities with populations of less than 1 million (Seto et al., 2014). Applying satellite data to urban growth at smaller scales could support urban planning and policies related to these growing sources of urban energy demand and resource use.

## ENERGY IMPACTS

Energy impacts on land, water, and air quality have long histories of regulation and management in environmental policy. Even for these well-established contexts, satellite data introduce new opportunities and challenges in connecting with decision frameworks. Extending the relevance of satellite data to greenhouse gas emissions is a growing area of research, recognizing the complexities in connecting space-based detection of gases with on-the-ground decision needs (Esparza and Gauthier, 2021).

### Land and Water Impacts

Land use and water represent two of the largest impacts of crop-based bioenergy production as well as mining and other infrastructure for fossil fuels and nuclear energy. Satellites offer the potential to track and monitor energy-related impacts on land and water, which are key to successful resource management and disaster response. Because bioenergy systems rely on large amounts of biomass feedstocks, typically grown on land, they can result in particularly large land and water impacts. These impacts include direct changes in land use as well as indirect impacts via price effects that lead to expansion or contraction of crops used for biofuels or other purposes. Land use associated with bioenergy systems can also have ensuing consequences for biodiversity, water quality and use, and $CO_2$ emissions (Berndes et al., 2013; Popp et al., 2014). Satellite data can inform assessments of these impacts, as well as emissions from bioenergy and fossil fuel infrastructure, including refineries and power plants.

Satellite data have been instrumental in tracking patterns in land use and land cover change associated with existing bioenergy development. For example, the expansion of corn ethanol production in the U.S. has led to increases in corn cultivation, with satellite data being used to monitor resulting changes in crop rotations, land conversion, and participation in land conservation programs (Brown et al., 2014; Motamed et al., 2016; Wright et al., 2017). These changes may also contribute to shifts in water quality, which can be monitored directly by satellites or modeled using satellite data on land use, climate, and other environmental determinants (Haag et al., 2009; Hendricks et al., 2014). Similarly, satellite data have been used to track the expansion of palm oil, intended for biodiesel and other market uses, across the tropics (Koh et al., 2011; Carlson et al., 2012). These data have helped identify solutions to stymie the widespread environmental consequences of palm oil on rainforests, biodiversity, and local communities (Rose et al., 2015; Leidner and Buchanan, 2018; Meijaard et al., 2020).

Satellite data can also support interventions to minimize the environmental impacts of energy infrastructure on natural habitats and existing land conditions. For example, a pilot study from the Electric Power Research Institute (EPRI) tested the use of satellite data in identifying the effects of energy infrastructure on monarch butterfly habitats and wetlands (Madsen, 2021)[5].

[5]EPRI Program on Technology Innovation: New Frontiers in Milkweed Detection — Evaluating the Potential of Satellite Data and Machine Learning. https://www.epri.com/research/products/000000003002016599.

Another analysis used satellite data to monitor impacts along Azerbaijan gas and oil pipeline right-of-ways (ROW) spanning 10 million square miles (Bayramov, 2013).

Satellite data have also been used to assess the impacts of energy systems on water quality, particularly those arising from thermal power plants (i.e., bioenergy, fossil fuels, and nuclear). For example, studies have used satellite data to estimate water demand (Luo et al., 2018), monitor thermal discharge from power plants (Wu et al., 2007), detect turbidity (Alkan, 2009), and estimate water quality impacts (Sridhar and Vincent, 2009). Remotely sensed data have also been used as inputs to advanced modeling and prediction of water quality outcomes from bioenergy production. Off the coast of the U.S., the size of the Gulf of Mexico hypoxic zone, the world's second largest oxygen-depleted "dead zone" (Dybas, 2005), can be tracked and modeled using satellite data (Haag et al., 2009), and contributions from changes in bioenergy-related land use can be estimated using satellite-based inputs (Donner and Kucharik, 2008; Hendricks et al., 2014). Similarly, satellite data have been used to track the size and occurrence of harmful algal blooms (Klemas, 2012; Shen et al., 2012) and estimate the contribution of bioenergy to water quality impairments (Hamada et al., 2015; Lin et al., 2015; Chen et al., 2017). Satellite data have also been critical in real-time monitoring of oil spills (see **Figure 6**).

Satellite-based assessments can inform water resources conservation and planning for energy and other uses (Bastiaanssen et al., 2012). For example, analyses of evapotranspiration can inform estimates of potential water use associated with bioenergy feedstock production (Bhattarai et al., 2017; Wagle et al., 2017). These estimates can also be compared to the evapotranspiration of alternative (e.g., food) crops or native ecosystems, and inform assessments of the overall water use intensity of bioenergy feedstocks relative to other energy systems and land uses (Sanders and Masri, 2016).

The ability of satellites to capture frequent observations of changes in land and water use creates exceptional opportunities to evaluate the causal outcomes of energy policies, many of which began after routine satellite data collection (Blackman, 2013; Donaldson and Storeygard, 2016). Publicly available, space-based data can provide transparency and credibility for certification schemes that go beyond industry-reported results. For example, the Roundtable for Sustainable Palm Oil (RSPO) certification schemes rely on satellite technology to strengthen fire prevention efforts and protect forests (RSPO, 2021). Bonsucro's certification scheme for sugarcane production, which is used as a feedstock for ethanol, also relies on satellite data to map changes in land use (Bonsucro, 2021).

## Health and Air Quality Impacts

A wide range of gas and particle species are emitted from fossil fuel combustion in the energy system, especially nitrogen oxides ($NO_x$), carbon monoxide (CO), and sulfur dioxide ($SO_2$), as well as suspended liquid and solid particles, referred to as particulate matter (PM). These traditional air pollutants represent the most direct linkage between energy policy and health outcomes. The World Health Organization (WHO) estimates that 92% of the global population lives in areas where air quality levels exceed WHO limits (World Health Organization, 2016), and 4.2 million people die each year due to outdoor air pollution[6].

In many ways, the experience of the air quality and health communities serves as a success story for satellite data integration into existing energy-related decision frameworks (Holloway et al., 2021). As satellite technology advanced to detect gases and particles in the atmosphere, early research highlighted the potential for these datasets to inform model evaluation, support improved emission inventories, and assess surface abundance of health-relevant pollutants. In 2011, NASA launched the first Applied Sciences team around the theme of air quality (Jacob et al., 2014), which was expanded to address health and air quality in 2016 (Holloway et al., 2018) and renewed in 2021. The three generations of these teams represent a systematic research and outreach enterprise, wherein applied research projects have advanced rapidly over the past 10 years, in collaboration with stakeholder partners.

These experiences highlight key areas where satellite data can inform energy-related air quality and health issues (World Health Organization, 2016). Nitrogen dioxide ($NO_2$) has emerged as perhaps the most useful air quality indicator from satellites, which has been used as an indicator of $NO_x$ emissions, including trends in $NO_x$ emissions associated with emission controls on power plants as well as transportation patterns, fuel shifts, and economic changes. As an example, satellite $NO_2$ from the TROPOMI instrument was used as an indicator of energy use changes during the early stage of the COVID-19 lockdowns in early 2020 (see **Figure 7**) (NASA Earth Observatory, 2020).

Because most $NO_2$ in the troposphere is emitted near the surface, the column abundance detected by satellites is well-correlated with concentrations detected by ground monitors (Goldberg et al., 2021). Furthermore, the short atmospheric lifetime of $NO_2$ limits mixing of the pollutant in the atmosphere, such that satellite images capture the sources of emissions and track closely with spatial patterns in combustion activities at the ground level. Satellite $NO_2$ has been used to evaluate health outcomes from $NO_2$ (Anenberg et al., 2022) and environmental justice dimensions of air pollution exposure (Kerr et al., 2021). $NO_2$ is also a key ingredient in ozone production near the surface, and thus an important factor in ozone control strategies (Duncan et al., 2010; Witman et al., 2014).

Many other chemical species observed from space bear relevance to energy emissions, air quality, and health. For example, satellite-derived $SO_2$ can be an important indicator of power plant emissions (Lu et al., 2013), satellite observations of CO show the impact of global pollution transport (NASA, 2015), and satellite observations of "aerosol optical depth" have been used quantify global exposure to fine PM (van Donkelaar et al., 2010). Beyond tracking fuel combustion, satellite data have been used to assess upstream emissions from energy processes, such as dust impacts of cropland expansion from bioenergy (Lambert et al., 2020) and air emissions associated with the pre-harvest sugarcane field

[6]World Health Organization. Air pollution. https://www.who.int/westernpacific/health-topics/air-pollution.


**FIGURE 6 |** Satellites were able to spot an oil slick from a major oil spill in Southern California in 2021. **(L)** is an image from October 2, 2021, from OLI on Landsat 8, and **(R)** is a SAR image from the ESA Sentinel-1B satellite. [Credit: NASA Earth Observatory image by Joshua Stevens, using Landsat data from the U.S. Geological Survey and modified Copernicus Sentinel data processed by the ESA (NASA Earth Observatory, 2021b)].

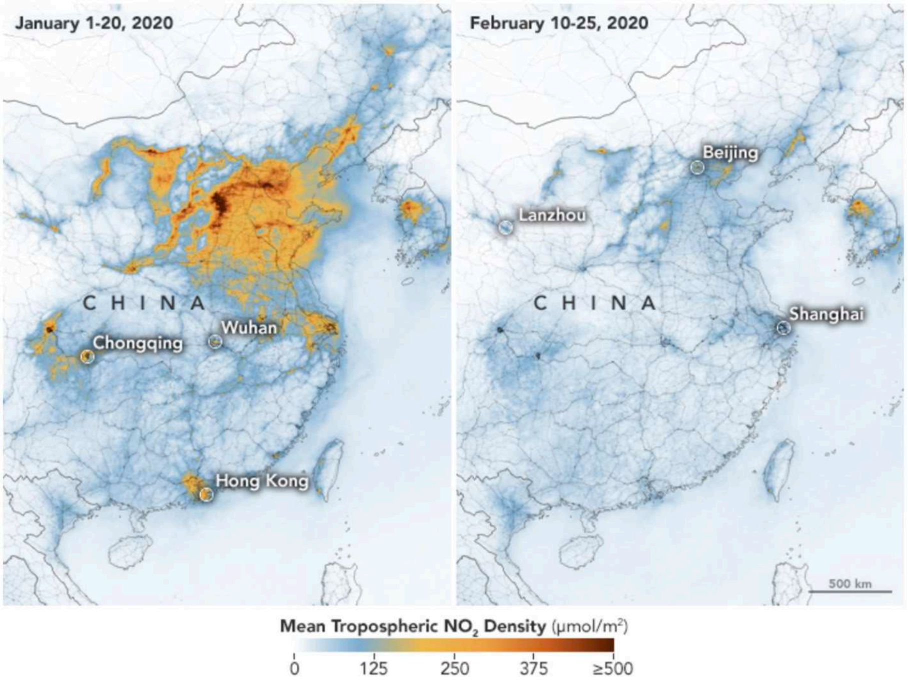


**FIGURE 7 |** Changes in $NO_2$ concentration due to COVID-19 lockdown in China using data collected from TROPOMI from ESA's Sentinel-5P satellite (Credit: NASA Earth Observatory images by Joshua Stevens, using modified Copernicus Sentinel 5P data processed by the ESA).

burning phase of ethanol production in Brazil (Tsao et al., 2012).

## Oil and Gas Emissions

Oil and gas operations release a wide range of chemical emissions, including volatile organic compounds (VOCs, associated with ozone formation and also posing direct health risks) and the powerful greenhouse gas methane. Both the federal government and some states in the U.S. are beginning to consider satellite data to assess oil and gas VOC emissions for regulatory purposes. A proposed rule in New Mexico incentivizes the use and development of new technologies for leak detection and repair (LDAR) such as remote monitoring via satellites or aircraft, aiming to increase the accuracy and speed of reporting as part of their ozone control effort. Colorado provides operators with the opportunity to submit an Alternative Approved Instrument Monitoring Method (AIMM) for identifying VOC ozone precursors. These changes provide the opportunity to include other monitoring methods as an alternative to current ground-based measurement approaches.

Methane emissions from oil and gas systems have been the subject of significant recent policy action. At the 2021 United Nations Climate Change Conference (COP26), more than 100 countries joined the U.S. and EU in launching the Global Methane Pledge, an initiative to reduce methane emissions by at least 30% from 2020 levels by 2030 (European Commission, 2021). Satellite-based inventory methodologies can play a crucial role in achieving these goals by providing timely data for monitoring and verifying country commitments. The United Nations Environment Program (UNEP) is supporting this effort through the International Methane Emissions Observatory (IMEO), which will use multiple data sources from satellites, ground-based sensors, and national and company inventories (UN Environment Programme, 2021). These data can be combined to identify and reconcile gaps and inconsistencies and enable global stakeholders to track whether emissions reductions are being achieved and take targeted action.

Satellites can monitor oil and gas infrastructure on a frequent basis with an emphasis on high-risk areas, quickly detecting very large emissions sources. The natural gas supply chain is characterized by super-emitter behavior, where a small percentage of sources are responsible for the majority of emissions. A meta-analysis of approximately 15,000 measurements from 18 individual studies in the U.S. showed that the largest 5% of methane leaks typically contribute over 50% of the total emissions by volume (Brandt et al., 2016), and similar phenomena have been observed for individual production sites (Zavala-Araiza et al., 2017) and across sources and sectors (Duren et al., 2019). A recent study also used satellite data to identify large methane releases from "ultra-emitters" worldwide (Lauvaux et al., 2022).

Policies targeting super-emitters could be a cost-effective strategy for reducing overall emissions (Ravikumar et al., 2020; Edwards et al., 2021). Multiple types of measurements can work together to assess methane emissions in a tiered system-of-systems approach, integrating space-based platforms with airborne instruments and ground sensors (Esparza and Mattson, 2021). This tiered approach can enable more complete monitoring, detection, and repair of emissions sources without the need to deploy an impracticably large number of ground-based sensors, consistent with other examples of using satellite data to complement other measurement approaches.

In recent years, greenhouse gas monitoring satellites from the private sector have complemented technology from government space agencies[7]. For example, the company GHGSat currently has three methane sensing satellites in orbit with spatial resolutions as low as 30 m, allowing for detection of point sources such as individual oil and gas wells. GHGSat has an ongoing collaboration with the Netherlands Institute for Space Research (SRON) whereby elevated methane levels detected by TROPOMI, which makes measurements in 2,600 km swaths at 7 km resolution, are followed up with high-resolution GHGSat imagery that can attribute these methane hot spots to specific facilities (European Space Agency, 2020).

In early 2019, a GHGSat satellite was imaging a natural source of methane emissions known as a mud volcano in the western part of Turkmenistan when it serendipitously discovered an enormous methane leak – assessed to have been 10,000 to 43,000 kg/h – from a compressor station at the nearby Korpezhe oil and gas field. Other nearby leaks of similar magnitudes were also identified. These were some of the largest methane leaks ever detected by satellite at the time. Archived TROPOMI data confirmed the magnitude of these emissions sources going back at least 14 months (Varon et al., 2019). GHGSat worked with the diplomatic community to identify the industrial operator and contact the relevant authorities, and for a period of time the leaks were stopped. However, in February 2021, another GHGSat satellite detected new leaks from eight natural gas pipelines and unlit flares in the Galkynysh gas field in Turkmenistan (see **Figure 8**) (Malik Naureen, 2021).

There are barriers to increasing the use of satellite data to inform policy on oil and gas emissions. For example, the EPA has had an alternative means of emission limitation (AMEL) program since 1977 (42 U. S., and Code § 7401, 1977), but the current AMEL application process is complex and requires EPA review prior to public notice and public hearing events. This complexity may limit the use of satellite data in satisfying regulatory requirements, such those targeting methane and VOC emissions from new and existing sources in the oil and gas sector.

## Energy-Related $CO_2$ Emissions

Accurate estimates of the distribution and magnitude of $CO_2$ emissions from energy systems are important for improving predictions of climate change, designing policies to reduce emissions, and monitoring and verifying their effects. Historically, anthropogenic $CO_2$ emissions have been inferred through bottom-up approaches using reported or estimated data on fuel consumption, emission factors, and

[7]Group on Earth Observations, Climate TRACE and World Geospatial Industry Council. Greenhouse Gas Monitoring from Space: A Mapping of Capabilities Across Public, Private, and Hybrid Satellite Missions. GEO Observations Blog http://www.earthobservations.org/geo_blog_obs.php?id=533.

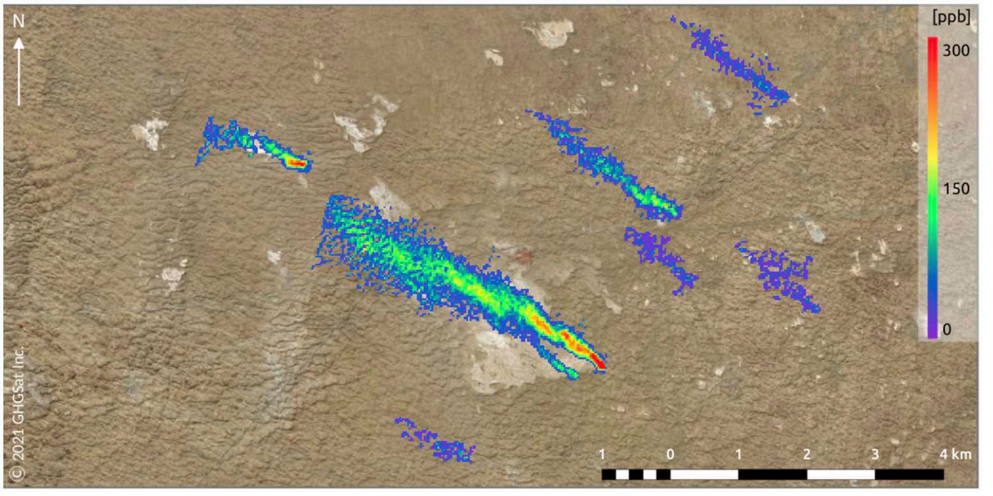


**FIGURE 8 |** Eight separate methane plumes captured by GHGSat in a single image, representing a total emission rate of about 10,000 kg/hour. Four of the larger plumes on the left are emissions from pipelines (likely problems with valves), with the remaining emissions from unlit flares.

fuel properties for thermal power plants, transportation, and industry. However, there are uncertainties in these data, even in high-income economies (Wheeler and Ummel, 2008; Gurney et al., 2019). For example, there is generally about a 20% difference between U.S. thermal power plant emissions estimated from fuel usage and those reported from a continuous emissions monitoring system (CEMS) program (Ackerman and Sundquist, 2008). Data uncertainties and gaps have prompted policymakers to look to satellite data to enhance tracking of greenhouse gas emissions and to monitor and verify reduction efforts.

The first space-based measurements of the global distribution of near-surface greenhouse gases were performed by an instrument called SCIAMACHY (European Space Agency, 2005), which operated aboard the ESA's Envisat satellite between 2002 and 2012. The first satellites dedicated to greenhouse gas measurements were GOSAT, launched by the Japan Aerospace Exploration Agency in 2009, and the Orbiting Carbon Observatory-2 (OCO-2), launched by NASA in 2014 (see example in **Figure 9**) (Yokota et al., 2009; Crisp, 2015). These were followed by TROPOMI aboard the ESA Sentinel-5P satellite, which has been in operation since 2017, as well as the GOSAT-2 satellite launched in 2018 and the OCO-3 instrument that was installed on the ISS in 2019. Tracking of greenhouse gas emissions with satellites is set to expand in the upcoming years: the Environmental Defense Fund (MethaneSat), the State of California (Carbon Mapper), and NASA (Geostationary Carbon Cycle Observatory, or Geocarb) are all planning launches of satellites to track emissions between 2022 and 2025 (Dennis, 2021). The growth in new dedicated satellite instrumentation, combined with existing measurements, may allow for easier independent monitoring, verification, and enforcement of the national emissions reduction commitments under Paris Agreement (Ganesan et al., 2019; Kaminski et al., 2022).

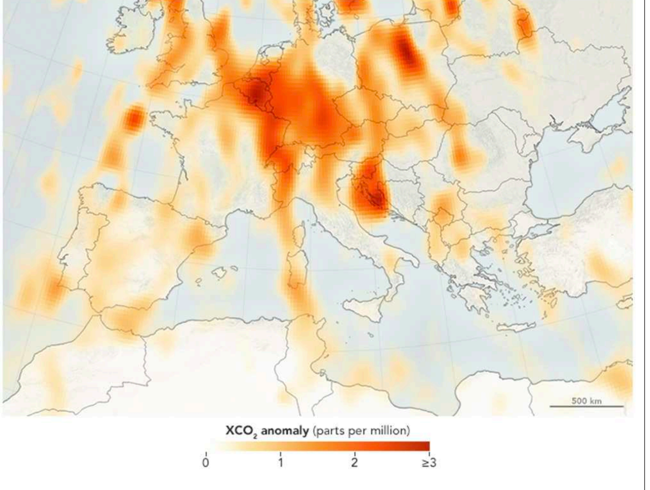


**FIGURE 9 |** Tracking human contribution to atmospheric $CO_2$ using data from NASA's OCO-2 satellite. Here, anomalies are shown from between 2014-2016. [NASA Earth Observatory maps by Joshua Stevens, using OCO-2 anomaly data courtesy of Hakkarainen et al. (2016) (NASA, 2016)].

Satellite observations of column-averaged $CO_2$ concentrations have demonstrated that, in some circumstances, satellites can provide top-down constraints on source emissions, but the capabilities of current satellite instruments are limited (Nassar et al., 2017, 2021; Hill and Nassar, 2019; Zheng et al., 2019; Wu et al., 2020). Data from GOSAT and OCO-2 do show statistically significant $CO_2$ enhancements over metropolitan regions (Kort et al., 2012; Schneising et al., 2013; Janardanan et al., 2016; Buchwitz et al., 2018; Wang et al., 2018; Reuter et al., 2019), and top-down methods have been applied to a few large thermal power plants (Bovensmann et al., 2010; Velazco et al., 2011), which are

some of the largest point sources of anthropogenic $CO_2$ (Janssens-Maenhout et al., 2019). A recent analysis presented the first quantification of $CO_2$ emissions from individual power plants using OCO-2 observations (Nassar et al., 2017). However, because of the narrow swath (~10 km at nadir) and 16-day repeat cycle of the sensor, the number of clear-day overpasses is too few for the development of a global $CO_2$ emissions inventory (Kiel et al., 2021; Nassar et al., 2021). The sparse sampling of the OCO-2 sensor will partly be overcome by the planned $CO_2$ imaging satellites that have denser spatial coverage, such as the $CO_2$ Monitoring mission (CO2M) and the GeoCarb instrument (Moore et al., 2018; Sierk et al., 2019).

An alternate method uses auxiliary satellite data, such as co-emitted $NO_x$, as a proxy for $CO_2$ emissions. Recent studies have shown that using $NO_2$ data for plume detection improves quantification of annual $CO_2$ emissions from point and urban sources as compared to $CO_2$ data alone (Kuhlmann et al., 2019, 2021; Reuter et al., 2019). This method takes advantage of the higher spatial resolution and spatiotemporal coverage of satellite $NO_2$, from which $NO_x$ emissions are inferred, and have been shown to compare well to independent observations (Beirle et al., 2011; Duncan et al., 2013, 2016; de Foy et al., 2015; Lu et al., 2015; Krotkov et al., 2016; Liu et al., 2016, 2017; Goldberg et al., 2019). This approach is particularly useful for identifying new combustion sources as they come online and changes in existing point sources and urban areas (Duncan et al., 2016; Krotkov et al., 2016). The highest resolution satellite instrument for $NO_2$ is TROPOMI (2017-present) (Levelt et al., 2006, 2018; Veefkind et al., 2012; Munro et al., 2016; Krotkov et al., 2017). $NO_2$ and satellite-based CO and $CO_2$ data can also provide constraints on emissions inventories and be useful in monitoring trends and understanding regional-scale combustion (Silva and Arellano, 2017; Goldberg et al., 2019; Liu et al., 2020; Park et al., 2021).

$CO_2$ emissions from individual power plants and large cities may also be inferred from satellite $NO_2$. For power plants, these calculations have been performed using linear relationships between reported $NO_x$ and $CO_2$ emissions by coal type, firing method, and emission control device (Liu et al., 2020). Ratios of $NO_x$ to $CO_2$ emissions derived from U.S. power plants, where power plants have CEMS stack-height emissions monitors, offer a reasonable approximation for power plants in other countries, especially where coal type is known (Zoogman et al., 2017; Kim et al., 2019; Timmermans et al., 2019). City-scale emissions may be inferred through related statistical approaches to fit a collection of satellite-observed $NO_2$ plumes and inferred $CO_2$ emissions (Goldberg et al., 2019). While conducted and validated in the U.S., these approaches show potential for estimating $CO_2$ emissions in other countries as well.

Moving forward, a synergistic combination of bottom-up and top-down approaches would likely provide the greatest constraint on global anthropogenic $CO_2$ emissions. CO2M will carry instruments to observe both $NO_2$ and $CO_2$, which will allow for the estimation of $NO_x/CO_2$ ratios, although these ratios may have large regional and technological uncertainties (Kuhlmann et al., 2021). It has been shown that satellite $NO_2$ and $CO_2$ data could be used to infer a ratio to allow the estimation of $CO_2$ emissions using TROMPOMI and OCO-2 data for an individual power plant (Hakkarainen et al., 2021). These methods ideally would be complemented by a database with region-specific $NO_x/CO_2$ ratios from CEMS measurements or other bottom-up sources.

## ENERGY RESILIENCE

Extreme weather events have long been a major risk factor for energy infrastructure, with climate change worsening these risks. Satellite data can provide a cost effective means for tracking vulnerable energy infrastructure, planning for new climate normals, and providing real-time support for operations and maintenance.

### Energy Resilience and Global Change

Power outages, infrastructure damage, and challenges with adequately managing energy demand are well-known consequences of extreme weather and weather-related disruptions, including storms, heat waves, wildfires, and flooding (IEA, 2021a). In the U.S., for example, blackouts from extreme weather events cost an estimated \$20 to \$55 billion annually (Nik et al., 2021), and hurricanes are a major cause of power outages that have contributed to substantial loss of life and infrastructure (Alemazkoor et al., 2020). Extreme heat stresses the electric grid, resulting in increased demand for air conditioning and a loss in transmission and distribution efficiency (Añel et al., 2017). In February 2021, historic snowfall and ice across Texas led to blackouts that left millions of people without power (Nazir, 2021). Transmission line failure caused by extreme wind or heat can also result in wildfires, as in the 2009 Australian “Black Saturday” fires, where line failures ignited one of the most disastrous bushfires in Australian history, resulting in 173 deaths and \$4 billion (Australian) in property damage (Mitchell, 2013).

Within the energy management sector, there is a strong push to design climate-resilient infrastructure that can continue operating or recover quickly after immediate shocks and adapt to long-term changes in climate and environmental conditions (IEA, 2021b). In the U.S., increased emphasis on embedding climate adaptation and resilience into federal programs could support investments in the energy sector. Efforts currently underway include the Biden Administration’s Executive Order 14008 on Tackling the Climate Crisis at Home and Abroad, Build Back Better Agenda, Infrastructure Investment and Jobs Act, and Justice40 Initiative, which focus on shifting energy supply to reduce environmental and health risks and support economic development for communities impacted by energy transitions (The White House, 2021a,b). Complementing these efforts, the Department of Energy (DOE) is deploying climate-resilient energy technologies nationwide, including in underserved communities (U.S. Department of Energy, 2021).

Satellite data can be used to better understand the impacts of a changing climate on energy infrastructure, advance the development of forecast models, and reduce the effort needed to assess environmental risks, which in turn can improve site-specific resilience planning (Leibrand et al., 2019). To support the climate adaptation and resilience efforts underway in the Biden

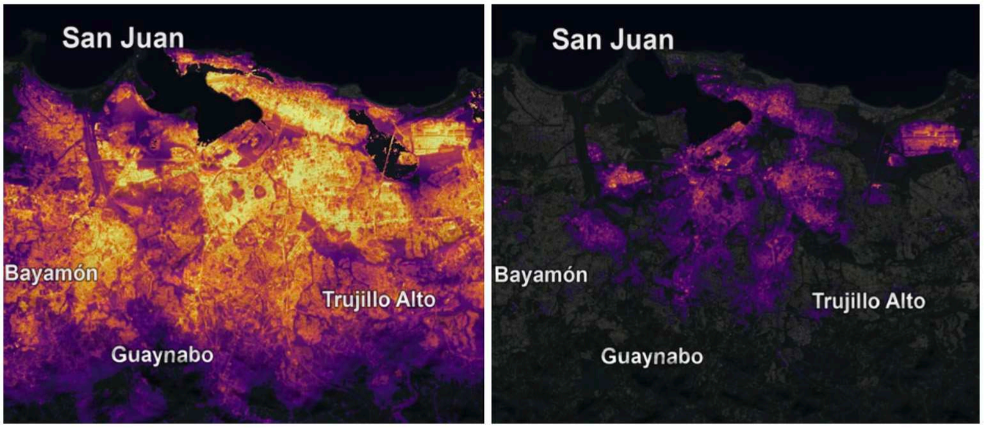


**FIGURE 10 |** Baseline (pre-storm) view of San Juan, Puerto Rico, nighttime lights **(L)** and average nighttime lights two months (Sep. 20 - Nov. 20, 2017) after Hurricane Maria **(R)**. (Credit: Kel Elkins, NASA Scientific Visualization Studio).

Administration, NASA and NOAA are planning to provide data and services to stakeholders to increase understanding of threats and vulnerabilities due to climate change (Margetta, 2021; US Department of Commerce, 2021). Satellite data can be used to inform planning to mitigate various energy infrastructure risks (Hauer and Miller, 2021). For example, several utility companies' wildfire mitigation plans use satellite data to monitor wildfire risks (Horizon West Transmission, 2021; Idaho Power, 2021; Pacific Gas and Electric Company, 2021; San Diego Gas and Electric Company, 2021; Southern California Edison Company, 2021), and satellite data has been used to identify vegetation encroachment and stressed or dead trees (Matikainen et al., 2016; Mahdi Elsiddig Haroun et al., 2020)[4,8].

Satellite data are also already being used to support disaster response in the energy sector. For example, in 2004, Eskom, South Africa's largest energy company developed a mobile fire alert system to mitigate line faults and provide near-real-time fire information. This system relies in part on NASA MODIS data and Meteosat Second Generation (MSG) data from the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) and is still in use today (Davies et al., 2008)[9]. MODIS data are also an integral part of NASA's Fire Information for Resource Management System (FIRMS), which integrates data from both MODIS and VIIRS instruments to deliver global active fire and hotspot data in near real time, within three hours of satellite observation (NASA, 2021).

Following Hurricane Maria's devastating impacts on Puerto Rico in 2017, NTL data from NASA's Black Marble product were used to understand the extent of power outages and characteristics of areas that withstood the greatest impact. These data were later used to monitor the effects of electricity restoration policies (see example in **Figure 10**), including how these policies can exacerbate inequality and unintentionally burden vulnerable populations (Romn et al., 2019). The high spatial resolution of Black Marble enables researchers to overcome four primary limitations of power outage data: timeliness, continuous data collection, consistent data across large geographic areas, and availability of data at a very fine spatial resolution (Romn et al., 2019).

[8]EPRI Identification of At-Risk Trees Using Satellite Imagery. https://www.epri.com/research/products/000000003002019050.

[9]Advanced Fire Information System (AFIS). AFIS. http://www.afis.co.za/.

## DATA DISTRIBUTION

Distribution of satellite data for use by decision makers and researchers is a continuing challenge, especially as the number and complexity of data products grows. While researchers and high-end data users may choose to navigate data distribution platforms, many stakeholders prefer GIS-enabled web interfaces developed for their application area. The most developed energy-specific platform for satellite data distribution is the NASA Prediction Of Worldwide Energy Resources (POWER) project. POWER has provided Earth observation data for energy applications since 2002, with the goal of improving the accessibility and use of NASA data to support community research in three focus areas: (1) renewable energy development, (2) building energy efficiency and sustainability, and (3) agroclimatology applications (Zell et al., 2008; Eckman and Stackhouse, 2012). POWER allows users to select community-specific parameters, units, time periods, and output formats to efficiently retrieve data. The output data can then be directly applied in decision support tools, modeling and forecasting packages, and as inputs to scientific research.

The solar energy parameters in POWER are compiled using multiple satellite data sources. Hourly to long-term averaged parameters are provided for each parameter and can be used to support applications such as solar cooking, sizing solar panels, and designing battery backup systems. The daily and hourly time series include the basic solar and meteorological parameters as well as additional calculated parameters such as diffuse and direct normal radiation. For example, a community solar installation in a rural village in West Africa appeared to be working poorly. POWER data revealed that the solar array was in fact performing

up to specifications, but cloudiness affected the available solar energy. Local management made the necessary adjustments to power usage and billing, drawing from data only available via satellite (NASA POWER and NASA ARSET, 2021). Similarly, a consultant responsible for solar installations at various locations in North Carolina uses the low latency data products to help assess changes in output (NASA POWER and NASA ARSET, 2021).

POWER data products have also been used to support a variety of energy system operation and maintenance decisions. For example, the Ottawa Renewable Energy Cooperative used the RETScreen Expert Clean Energy Technology software suite, which directly links the POWER web suite, to assess the potential benefits of paying for snow removal for a rooftop PV system by comparing lost generation to the building's actual load (NASA POWER and NASA ARSET, 2021). NASA's Office of Strategic Infrastructure also uses RETScreen for building energy management (Rosenzweig et al., 2014). Additionally, satellite estimates suggest that increases in the solar irradiance in the maize growing regions of the U.S. from the late 1980's through about 2012 were responsible for 27% of the productivity increase observed during this time period, relevant to corn-based biofuels (Tollenaar et al., 2017). Finally, the value of packaging correlated solar, wind, and other meteorological parameters has been demonstrated for a smart energy management system for hybrid solar-wind-biomass systems (Bhattacharjee and Nandi, 2021).

## DISCUSSION

Applications of satellite data are growing across a wide range of energy policy and planning problems. Recent developments are increasing the potential for satellite data to support energy decision-making, with new public and private satellites being launched, advances in data processing techniques, and efforts by government and private organizations to increase uptake in new user communities. With more complete spatial and temporal coverage, satellite data can fill gaps in traditional data sources. Often the value of space-based data is greatest through integration with existing data and decision tools. Many types of satellite data have been collected for years, enabling analysts to track changes in energy supply, demand, and impacts over time and evaluate the effectiveness of policy interventions. While collecting satellite observations entails high fixed costs, the marginal costs are generally low, especially for datasets that are freely available to the public. Since data collection is remote, it also does not directly disturb local communities or the environment.

Our review points to many applications and opportunities for further use of space-based measurements. For energy supply, this includes resource potential and risk assessment to inform siting, development, and maintenance of energy infrastructure as well as real-time resource availability to support grid management and ensure reliability of supply. For energy demand, it includes energy use patterns to predict energy needs and identify locations with unserved demand. For energy impacts, it includes the effects of energy use on climate, air quality, and water and land systems, as well as monitoring efforts to reduce these impacts. Satellite data are also playing an increasing role in supporting investments in energy resilience, both in advance and in the aftermath of disruptions to energy access. The expansive coverage of many measurements allows for global indexing of critical metrics, and the increase in temporal resolution of new products means that satellite data can be used to track progress toward policy commitments to reduce energy-related emissions, increase energy access, and support sustainable energy transitions around the world.

The technical limitations in the use of satellite data for energy applications are primarily driven by insufficient spatial and temporal resolution. For example, polar orbiting satellites such as the Landsat 8 Operational Land Imager (OLI) and the recently launched Landsat 9 Operational Land Imager 2 (OLI-2) provide radiance measurements that are high spatial resolution (30 m) and multispectral (visible, near-infrared, and shortwave infrared bands). These measurements are suitable for land use characterization at urban and individual agricultural field scales. However, the 16-day repeat cycle, relatively narrow swath width (165 km), and likelihood of cloudy scenes limits temporal sampling to typically a single observation at one location each month, which does not allow for rapid responses to changing conditions. The European Sentinel-2 MultiSpectral Instrument (MSI) partially addresses these limitations with a 5-day repeat cycle and higher spatial resolution (10 m for the visible channels and 20 m for near-infrared and shortwave infrared). Other polar orbiting instruments, such as VIIRS, have more channels and larger swath widths (3000 km) and can observe the entire planet each day. However, VIIRS has significantly lower spatial resolution than either Landsat or Sentinel-2.

Unlike polar orbiting satellites, geostationary satellites continuously observe the same area and consequently have very high temporal sampling, and a constellation of geostationary satellites can allow for near global, continuous sampling of the Earth throughout the day. The U.S. Advanced Baseline Imager (ABI) on GOES East and West, Japanese Advanced Himawari Imager (AHI), and European Meteosat Third Generation (MTG) are all third-generation geostationary instruments with similar retrieval capabilities as VIIRS but even coarser spatial resolution. A new generation of instruments such as the recently launched Geostationary Environmental Monitoring Spectrometer (GEMS), Tropospheric Emissions: Monitoring of Pollution (TEMPO), and the European UltraViolet/Visible/Near-Infrared (UVN) instrument will provide the first geostationary hourly ultraviolet radiance measurements suitable for a wide variety of energy applications, from tracking photosynthetic activity for biofuel production to monitoring $NO_2$ emissions from fossil fuel combustion. The GeoCarb instrument will provide similar measures of photosynthetic activity as well as geostationary $CO_2$, CO, and $CH_4$ retrievals over North America.

Combining high spatial resolution polar orbiting measurements with high temporal resolution measurements from geostationary satellites will create unprecedented opportunities for energy policy and planning. For example, accurate short-term cloud forecasts are critical for optimizing electric power generation and load balancing. Improved use

of geostationary cloud measurements for solar PV forecasting could include data assimilation for short-term surface irradiance forecasts and advanced pattern recognition estimates of cloud motion. Using satellite data for improved monitoring and prediction of droughts (in particular, flash droughts) and resulting changes in photosynthetic activity could have significant impacts on improving biofuel production efficiency. Satellite data with high spatial and temporal resolution also can uncover patterns of energy injustice. For example, new satellite-based research can help us understand who has access to energy infrastructure and the reliability, quality, and impacts of energy services for different groups. With the ability to monitor changes over time, we can also assess equity in energy transitions.

Beyond spatial and temporal resolution, analysts must also carefully consider the appropriateness of satellite data for energy policy and planning applications. It is particularly important to understand the distribution of potential errors in satellite measurements when they are used as a proxy for energy-relevant variables, and how these errors affect causal inference (Jain, 2020). For example, NTL datasets measure nighttime luminosity but are often used to estimate energy use and access, economic activity, and other variables. This approach can lead to biased inferences on the effects of policies if NTL data undercounts energy access in areas with intermittent service or underestimates economic activity in high luminosity areas due to saturation effects. Other types of errors can also be systematic, such as when agroforestry or plantations are classified as tree cover or when small-scale logging is undetected, which may lead to an underestimate of the effects of policies on forest loss. These challenges underscore the importance of data validation and the value of combining other types of data with satellite measurements to create a more complete picture of the energy system.

While researchers are actively working to address the technical limitations of satellite data for energy applications, addressing social and structural barriers will be equally important. While social science studies specifically on the use of satellite data for decision-making are more limited, in the case of air quality – especially for policy organizations implementing the Clean Air Act in the U.S. – a range of social and structural as well as technical barriers impede data use relative to traditional monitoring and assessment methods (Milford and Knight, 2017). Satellite data do not fit with decision and policy frameworks in a clear manner, and users have expressed uncertainty about whether data will be accepted for regulatory purposes. Research also indicates a number of social barriers to satellite data use, including difficulty finding data, data formats that are unfamiliar or difficult to use, and lack of staff time, training, and expertise to acquire and process data. Two-way dialogue between end-users and satellite experts has helped identify specific areas where space-based data can contribute effectively to information needs.

Collaboration between researchers with expertise in satellite data analysis, energy systems and policy, and a broader set of social science disciplines will be essential to realizing the potential for satellite data to support energy decision-making. Research has pointed to the importance of active communication between experts and decision-makers and investing in translational work to bridge the gap between scientific data and decision processes (Cash et al., 2003; Klemun et al., 2020). Researchers themselves can engage in this boundary work – for example, NASA encourages engagement with the full satellite data application process through its Application Readiness Levels (ARLs), which range from initial discovery to full integration of satellite data into a partner's decision-making systems and processes. However, research also points to the vital role of boundary organizations and boundary objects (including data portals, interactive maps, and training workshops) in facilitating this work. Several organizations are actively working to enhance the usability of satellite data for energy applications.

Satellite applications for energy planning and policy are growing rapidly, with novel information needs to support sustainable energy transitions, a suite of new satellites recently launched or planned to be launched soon, and advances in methods for analyzing satellite data products and translating the results into useful information for energy decision-making. Our review suggests that, while there are many energy application areas where satellite data are already playing an important role, there is significant untapped potential to apply satellite data to support decision-making around energy supply, demand, impacts, and resilience. As advances in satellite data analysis open up new opportunities to support decision-making, active dialogue between experts in satellite data and energy planning and policy, as well as decision-makers across energy sectors, will be essential to maximize the usefulness of satellite data for sustainable energy transitions.

## AUTHOR CONTRIBUTIONS

MRE led the conceptualization, organization, and editing of the review paper with TH and RBP. All authors drafted sections of the paper, edited the final manuscript, and approved the submitted version.

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